Behind-the-Meter Disaggregation of Residential Electric Vehicle Charging Load

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***Abstract*—With the rapidly evolving penetration of electric vehicles (EVs) in power distribution systems, a major issue that utilities face is the lack of visibility into the charging behaviors of the behind-the-meter (BTM) EVs. Knowing the BTM EV charging behaviors can greatly enhance utilities' system planning and operation efficacy. In this paper, the problem of disaggregating BTM EV load traces from smart meter data traces is studied. Based on the characteristics of typical EV charging traces, three interdependent sub-problems are formulated: a) Detecting the presence of BTM EVs, b) Estimating the EV charging rate, and c) Detecting the EV charging periods. A unified iterative algorithmic framework is developed to solve all three sub-problems. Importantly, the proposed algorithms do not assume or utilize the knowledge of ground truth EV load traces but estimate BTM EV load traces in an "unsupervised" fashion. Numerical evaluation is conducted based on real-world 15-minute interval smart meter data from Austin, TX, and demonstrates great performance achieved by the proposed algorithms.**

I. Introduction

Our transportation system is undergoing a major transition with electrification as witnessed by the rapid increase of the adoption of electric vehicles (EVs). This however brings new and emerging challenges to the electric utilities as they strive to ensure reliable and efficient operation of power distribution systems [1], [2]. A major issue many utilities face is that they often have poor visibility into the charging behaviors of the EVs in the distribution system. In particular, in residential homes, utilities typically do not have access to data from dedicated sensors of EV charging activities. Such poor visibility of the EV charging behaviors hinders the utilities' objective to effectively plan and operate power distribution systems with significant penetration of EVs. On the other hand, there has been steadily growing smart meter deployment in utilities all around the world. By potentially extracting relevant information from the smart meter data, this presents a great opportunity for utilities to improve their visibility of EVs in their systems. Notably, however, as EVs are typically connected "behind the meter", no separate metering of EV charging is available to utilities, but the *total* load measured by smart meters.

To derive useful information about BTM EV charging from smart meter data, our objective is to disaggregate smart meter data traces into EV charging traces and non-EV/regular load traces. If successful, the utilities can then utilize the disaggregated data traces to better perform key planning and operation tasks such as system hosting capacity analysis, load forecast, and running effective demand response programs.

There have been a large number of works on nonintrusive load monitoring (NILM) that disaggregates smart meter measurement to obtain energy usage information of different appliances without installing BTM sensors (cf. [3], [4] among others). Among the works studying EV loads, some studies focus on detecting the presence of BTM EVs [5], [6]. For disaggregating EV charging loads in residential homes, supervised learning approaches are studied in [7], [8], [9], [10]. For unsupervised learning approaches, A pattern recognition based approach is developed in [11] for EV load estimation and evaluated based on simulation data. A training-free algorithm is proposed in [12] for EV load estimation, where an algorithm is developed to mitigate the interference from AC loads by filtering out spike trains generated by AC loads. A similar filtering step is also employed in [13], where a statistical model of EV charging for EV load estimation is established. Notably, however, all these algorithms (supervised and unsupervised) are developed based on smart meter data collected at 1-*minute intervals*. In contrast, this paper does not assume the availability of 1-minute interval data, but only 15-*minute interval* data which are the typical case in most utilities with smart meters. Working with 15-minute data however brings unique challenges as we can no longer exploit the rich 1-minute level data features of various appliances.

In this paper, we develop a novel suite of algorithms that disaggregate BTM EV charging load traces from the total load traces measured by smart meters. Publicly available temperature information is also used as input. Importantly, the algorithms do not assume or utilize any knowledge of the ground truth EV charging traces. Such "unsupervised" nature of the approach ensures that our algorithms are widely applicable in practice. The contributions of our work are summarized as follows:

- Our approach is a holistic one that jointly detects the presence of BTM EV and estimates (if an EV exists) the BTM EV charging trace.
- The proposed algorithms are "training-free" (cf. [12]).
- To the best of our knowledge, the proposed algorithms are the first that demonstrate excellent performance with data collected at 15-minute intervals (as opposed to more granular data such as 1-minute). This allows our algorithms to be readily applicable to most real-world smart meter systems.

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II. Problem Formulation

We consider smart meter data collected from a set of residential customers. A customer can possibly have a BTM EV. For a customer k, its smart meter measures its (total) load:

$$l_k(t) = d_k(t) + e_k(t), \tag{1}$$

where $l_k(t)$, $d_k(t)$, $e_k(t)$ are the (total) load, regular/non-EV energy demand, and the EV charging load at time t, respectively. For customers who do not have an EV, their corresponding EV charging loads would be zero at all times. In this paper, we consider that the smart meter data are collected at discrete time instances at every 15 minutes, which is typical in utilities' practices.

Our objective is to disaggregate the load trace $l_k(t)$ into $d_k(t)$ and $e_k(t)$. In particular, we develop algorithms that perform this disaggregation *based on the smart meter measurements* $\{l_k(t)\}$ *only, without any separate behind-the-meter measurements*. As $l_k(t)$ is measured, our objective is equivalent to *estimating the BTM EV charging trace* $e_k(t)$.

To begin with, we observe in the real-world data set [14] the following unique property of EV charging traces:

Remark 1 (Constant Charging Rate of an EV)**.** *For a customer with a BTM EV, when the EV is charging, its charging rate is typically closely around some constant, e.g.* 3.3 *kW [15][16].*

We denote the constant charging rate of customer k by E_k. Based on the above observation, BTM EV charging trace estimation is equivalently transformed into two sub-problems: a) estimating the *constant charging rate*, and b) detecting the *charging periods* of the EV, i.e., in which periods of time the EV is charging. As such, the EV charging trace can be modeled (approximately) as follows: in periods in which EV is charging, $e_k(t) = E_k$; otherwise, $e_k(t) = 0$.

In light of this, in order to perform BTM disaggregation of EV charging load trace for a customer k, the following three related problems need to be solved:

- **EV presence detection**: We do not assume any prior information about whether a customer has a BTM EV or not, since such information is often not readily available to utilities. Thus, it is essential to distinguish customers who have BTM EVs from those who do not.
- **Charging rate estimation**: For a customer identified as having a BTM EV, we estimate its (approximately) constant charging rate (cf. Remark 1) which depends on the levels of charging devices and the types of EVs.
- **Charging period detection**: For a customer identified as having a BTM EV, with an estimate of its near-constant charging rate, we detect the periods of time in which the EV is charging.

III. Algorithm Design

In this section, we introduce the methodology and algorithms for disaggregating the load $l_k(t)$ into regular/non-EV demand $d_k(t)$ and EV charging load $e_k(t)$. Our approach is to employ variations of *a unified algorithmic framework* for all three problems – EV presence detection, charging rate estimation, and charging period detection – with potentially different sets of algorithm parameters.

A. Data Preprocessing

First, we perform a step of data preprocessing as employed in [12] to identify and remove the load traces of air conditioning (AC) from the total load trace $l_k(t)$. The reason is that the AC loads may have similar magnitudes as EV charging, and removing them by recognizing their unique properties can significantly reduce the difficulties of estimating $e_k(t)$. AC loads generally exhibit two patterns: a) spike trains (i.e., fluctuating rapidly with a short duration), and b) AC lumps (i.e., fluctuating slowly with longer duration, see Fig. 1.(b) in [12]). This data pre-processing step aims to filter out AC spike trains from the load trace: The intuition is to find clusters of spikes where the duration of each spike is relatively short and adjacent spikes should not be too far away from each other. Due to space limit, we refer the reader to [12]) for the detailed algorithm for filtering out AC load spikes. We note that, while this pre-processing step works best with 1-minute data as in [12], it also works to some extent with 15-minute data. This is because, for a relatively significant fraction of the AC load spikes, their widths and the time gaps in between them have lengths that can be captured in 15-minute data.

B. EV Presence Detection

For a customer, we do not know beforehand whether there is a BTM EV or not. Our high-level approach is to a) assume as if there is a BTM EV, and jointly estimate the charging rate and detect the charging periods, and then b) perform statistical tests on the obtained results to make a detection decision on whether this customer indeed has an EV.

1) Daily Regular (Non-EV) Load Profile: First, we form an initial estimate of the daily *regular (non-EV) load profile* (which will be updated iteratively later), denoted by $\hat{d}_k(t)$. Specifically, our algorithm works as follows: *for each month*,

- *Minimum Load*: We form an estimate of the *minimum load* of the customer: $l_k^{\min} = \min_t l_k(t)$. This represents the "base load" of the customer even if there is little to no activity at home.
- *Non-Charging Periods*: Among all the time slots in the data, we select those time slots that clearly do *not* have an EV charging by selecting those t such that $l_k(t) < \hat{E}_k + l_k^{\min}$, where $\hat{E}_k$ is a charging rate estimate. The initial value of $\hat{E}_k$ is set to be 3kW for our data set, a conservatively low value.
- *Daily Regular/Non-EV Load Profile*: For every time index in a day (e.g., 10:00 am), we collect all the non-charging time slots selected above that share this index and compute the average as the *typical regular/non-EV load* at this time of a day. Accordingly, a daily regular/non-EV load profile $\hat{d}_k(t)$ is formed for this month.

2) EV Charging Period Detection: Next, given the fact that the EV charging rate is very significant compared with typical regular/non-EV loads, we detect the charging periods of this customer by exploiting the following two observations:

- *Change Point Detection*: Given the underlying smoothness of the regular load, an onset of EV charging tends to lead to a significant and immediate increase of the load $l_k(t)$. Similarly, the end of EV charging tends to lead to a significant and immediate decrease of the load $l_k(t)$.

- *Sufficiently Higher than Regular*: When an EV is charging, the load $l_k(t) = d_k(t) + E_k$ is likely significantly higher than the daily regular load profile estimate $\hat{d}_k(t)$.

We then detect a period of time as a charging period if both of the following conditions are satisfied: a) the first time slot in this period sees a sufficiently significant load increase, and the last time slot sees a sufficiently significant load decrease, and b) during this period of time, a sufficiently large fraction of the time slots see loads that are sufficiently higher than the estimated regular load profile $\hat{d}_k(t)$. The thresholds used in making these decisions are set based on the estimated charging rate $\hat{E}_k$.

Algorithm Description: We now describe in detail the proposed algorithm for EV charging period detection. To capture a sudden increase or decrease of the load, we introduce the following two variables:

$$\Delta_1 l_k(t) = l_k(t) - l_k(t-1) \tag{2}$$

$$\Delta_2 l_k(t) = l_k(t) - l_k(t-2) \tag{3}$$

The reason that $\Delta_2 l_k(t)$ is needed is a nuanced one: a) when an EV starts to charge at the beginning of time slot t, a significantly positive $\Delta_1 l_k(t)$ can be observed, but b) when an EV starts to charge only toward the end of time slot t, the load increase may not lead to a significantly positive $\Delta_1 l_k(t)$, but surely a significantly positive $\Delta_2 l_k(t+1)$. The similar phenomenon can be observed when an EV stops charging. In our algorithm, we use *change point status* $cps(t)$ to denote whether time slot t is identified as a potential start or end of a charging period, determined according to the following rule:

$$cps(t) = \begin{cases} 1 & \text{if } \Delta_1 l_k(t) \text{ or } \Delta_2 l_k(t) > cps_{th} \\ -1 & \text{if } \Delta_1 l_k(t) \text{ or } \Delta_2 l_k(t) < -cps_{th} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where cps_{th} is a threshold, an algorithm parameter.

Next, a time slot is more likely to have an EV charging if the load is significantly higher than usual. On the other hand, any time slot with a load lower than $\hat{E}_k$ is very unlikely to have an EV charging. In our algorithm, we use *charging status* $cs(t)$ to denote whether time slot t is identified to be within a charging period, determined according to the following rule:

$$cs(t) = \begin{cases} 1 & \text{if } l_k(t) > \\ & \quad \max(\hat{d}_k(t) + cs_{th}, \hat{E}_k + l_k^{\min}) \\ -\inf & \text{if } l_k(t) < \hat{E}_k \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where cs_{th} is a threshold, another algorithm parameter. Utilizing $cps(t)$ and $cs(t)$, potential start and end points of EV charging periods can be then identified. A *potential* start point of a charging period i, denoted by s_i, is defined if $cps(s_i) = 1$ and $cs(s_i) = 1$, and a *potential* end point e_i is defined if *either* $cps(e_i) = -1$ and $cs(e_i - 1) \leqslant 0$, *or* $cps(k) = -1, k = e_i, e_i+1, e_i+2$. The rationale is as follows. When an EV stops charging, the total load consumption will either be reduced to a low level if few other appliances are in use, or if not, at least a load decrease tends to be observed (which can be reliably detected with the above rule).

Next, we use $cs(t)$ to construct an *accumulator rule* [17] to further decide whether a potential charging period is an actual charging period. We set the initial value of the accumulator as 2. We then compare the actual load of all the time slots with the regular load profile within each identified potential charging period $[s_i,e_i]$. The accumulator will increase by 1 if $cs(t) = 1$, and decrease by 2 if $cs(t) = 0$. The accumulator will stop counting and return false when it becomes negative or if $cs(t) = -\inf$, i.e., when the load in a time slot in this potential charging period is lower than $\hat{E}_k$. The set of detected charging periods $\{[s_i,e_i]\}$ is denoted by $\hat{\mathcal{C}}$.

Algorithm 1 EV Presence Detection

1: **Input**: Customer load trace $l_k(t)$
2: Initialize $\hat{E}_k$=3kW
3: Construct regular load profile $\hat{d}_k(t)$ for each month (cf. Section III-B1)
4: **for** $epoch$ in 1 to $maxiter$ **do**
5: Detect charging periods by using Algorithm 2.
6: Update $\hat{d}_k(t)$ and $\hat{E}_k$.
7: Set $\hat{E}_k = \max(\hat{E}_k, 3kW)$
8: Go back to line 5 and detect the charging periods with the newly estimated regular load profile $\hat{d}_k(t)$ and charging rate $\hat{E}_k$ again.
9: **end for**
10: Perform statistical tests based on the detected charging periods (cf. Section III-B6).
11: **Output:** EV presence detection decision

Algorithm 2 Charging Period Detection

Input: Customer load trace $l_k(t)$, estimated charging rate $\hat{E}_k$, estimated regular load profile $\hat{d}_k(t)$
Calculate $\Delta_1 l_k(t)$ and $\Delta_2 l_k(t)$.
for t in 1 to T **do**
Determine change point status for time slot t (4).
Determine charging status for time slot t (5).
Update $\hat{\mathcal{C}}$ with any newly detected (s_i,e_i).
end for
for (s_i,e_i) in $\hat{\mathcal{C}}$ **do**
Run an accumulator (cf. Section III-B2) to examine this potential charging period and update $\hat{\mathcal{C}}$.
end for
Perform post-detection filtering of $\hat{\mathcal{C}}$.
Output: Detected charging periods

3) Post-Detection Tests and Filtering of Charging Periods: Next, we further examine these detected charging periods based on the following idea: within a detected charging period, the regular/non-EV load should behave statistically similarly to that immediately before and after this period. Accordingly, we use one-sided hypothesis testing to further remove false positives among the detected charging periods. Specifically, for a detected charging period $[s_i, e_i]$, we test if each $l_k(t) - \hat{E}_k, \forall t \in [s_i, e_i]$ follows a normal distribution $N(\mu, \sigma^2)$ — the "null hypothesis", where μ and σ^2 are the mean and variance of all the load measurements within the 2-hour window before and that after $[s_i, e_i]$. Given the length of $[s_i, e_i]$ (and hence the number of samples to test), we employ Bonferroni correction to control the "family-wise error rate" (FWER), i.e. the probability that at least one tested sample rejects the null hypothesis when the null hypothesis is in fact true. With the controlled FWER, the detected charging period will be removed from $\hat{\mathcal{C}}$ if any sample in it fails the test.

4) EV Charging Rate Estimation: With the set of all the charging periods detected, an estimate of the EV charging rate can then be formed by

$$\hat{E}_k = \frac{1}{|\hat{\mathcal{C}}|} \sum_{[s_i,e_i] \in \hat{\mathcal{C}}} \max\left(\Delta_1 l_k(s_i), \Delta_2 l_k(s_i)\right), \tag{6}$$

Where $\max\left(\Delta_1 l_k(s_i), \Delta_2 l_k(s_i)\right)$ denote the load increase when an EV starts charging. Precisely speaking, we only use the middle 50% of the load increases (from 25% quantile to 75% quantile) in the data to compute the above average so that the outliers can be excluded.

5) An Iterative Procedure: With the newly detected charging periods and the estimated charging rate, we employ an *iterative procedure* to refine these results:

a. Update the set of *non-charging periods* by selecting all the time slots *not* in the detected charging periods. Update the daily regular/non-EV load profile estimate $\hat{d}_k(t)$ (cf. Section III-B1).
b. Detect the charging periods based on the newly estimated regular load profile and the charging rate.
c. Update the charging rate estimate $\hat{E}_k$ (6). Go back to Step a.

6) Statistical Tests for EV Presence Detection: After sufficient iterations of the above procedure, based on the final regular load profile estimate $\hat{d}_k(t)$ and the detected charging periods $\hat{\mathcal{C}}$, we compute the following set of differences $\left\{l_k(t) - \hat{d}_k(t), \forall t \in \hat{\mathcal{C}}\right\}$ (i.e., the raw estimates of charging rates). We then make a decision on whether this customer indeed has a BTM EV by checking several statistics of this set of differences, including the *total number of samples, the mean, the median, and the average temperature (observed from weather data) over these samples.* The ideas are the following:

- The detected charging periods for a customer with an EV should contain mostly "true positives", (i.e., correctly detected charging periods), whereas the detected charging periods for a customer without an EV must all be "false positives". What we exploit here is the *difference between the statistical behavior of true positives and that of false positives*.
- The detected charging periods for a customer with an EV should be relatively evenly distributed across times of different temperatures. In contrast, false detection caused by the AC (or furnace) load would tend to concentrate in times of noticeably high (or low) temperatures.

For a customer with a BTM EV, it is expected that a) the number of samples in $\hat{\mathcal{C}}$ will be relatively large as it tends to include all the true charging periods, (e.g. charging at least 2 hours/week on average), b) the mean and the median will fall within an expected range of EV charging rate (e.g., between 3 kW and 4 kW [12]) as the differences are induced by true EV charging events, and c) The average temperature over the detected charging periods is moderate (e.g., between the 20% and 80% quantiles of the temperatures).

In contrast, for a customer with no BTM EV, all the detected charging periods are *false positives*, and the differences computed have nothing to do with an actual EV charging rate. As such, it is expected that a) the number of samples will be fewer as only false positives are included, b) the mean and the median may not fall within the normal range of EV charging rate as the differences are purely due to idiosyncrasies irrelevant to EV charging, and c) in case many false positives are caused by using AC (or furnace), the average temperature over these false positives will be noticeably high (or low). In Section IV, we will demonstrate the effectiveness of using such statistics for EV presence detection.

C. EV Charging Rate Estimation and Charging Period Detection

Once the EV presence detection decisions are made, we can partition the customers into those who have BTM EVs and those who do not. For each customer who has an EV, we then estimate the charging rate and detect all the charging periods. As shown above, in the algorithm for detecting EV presence, these two tasks are in fact already solved as sub-problems. As such, the same algorithmic framework is used for solving these two tasks. Still, modifications and new elements are introduced in the algorithm design to further enhance the performance.

a) Cross-Customer Similarity: In estimating customer k's regular/non-EV load profile, we further utilize those customers *without EV* to form an estimate by averaging their load profiles, as their loads are completely regular/non-EV loads. We note that, this was not possible when detecting EV presence, as we did not yet know which customers do not have EVs at that point. We then combine the original regular load profile estimate based on customer k's own data (cf. Section III-B) with the estimate based on the similarity between customer k and those customers without EV, so that an improved regular load profile estimate is obtained.

$$\hat{d}_k(t) \leftarrow (1-\alpha)\hat{d}_k(t) + \alpha \hat{d'}_k(t), \tag{7}$$

where $\hat{d'}_k(t)$ is the average regular load profile of customers who do not have EVs. In our numerical experiment, α is set to be 0.1.

b) Conservative Charging Period Detection for Accurate Charging Rate Estimation: Importantly, we note that estimating the charging rate and detecting the charging periods can be viewed as *two distinct objectives*, each of which can utilize its *own tailored algorithm*. Recognizing this, one useful technique to improve the performance of charging rate estimation is to set the algorithm parameters so that the *false positive rate* (FPR) is minimized, at the expense of a lower *true positive rate* (TPR). The rationale is the following. When estimating the constant charging rate, false positives often lead to much larger errors than true positives. If we can minimize the number of false positives (e.g., by setting the detection criteria harsher, i.e., detecting the charging periods more conservatively), even if it also inevitably leads to fewer true positives, as long as the total number of true positives is still reasonably large, the charging rate estimation will be improved.

c) Employing the Estimated Charging Rate for Charging Period Detection: After the EV charging rate is estimated, the final task is charging period detection. Here, since we already have a very accurate estimate of the charging rate, we will no longer update it as in the joint charging rate estimation/charging period detection algorithm in Section III-B. Instead, we will simply employ and fix the value of the estimated charging rate, and just run the other steps of the procedure (i.e., iterations of regular load profile estimation and charging period detection) to detect the charging periods. Empirically, we use the following post-detection correction to further enhance the performance:

$$\hat{\mathcal{C}} \leftarrow \{(s_i - 1, e_i + 1), \forall (s_i, e_i) \in \hat{\mathcal{C}}\} \tag{8}$$

These two extra time slots included serve as the “warm up” and “cool down” stages of a charging period.

IV. Data-Driven Evaluation

In this section, we evaluate the performance of the proposed algorithms based on a real-world data set from Pecan Street Inc. [14]. We note that, while there are three types of EVs with different charging rates, our study focuses on the most challenging type with the lowest charging rate (between 3 to 4 kW) which is also the only type with sufficient data in this data set for a comprehensive evaluation. The lowest charging rate presents the most challenge as it results in the lowest “signal to noise ratio” for detection and estimation. Specifically, the data was collected from 23 customers (5 of which with EVs and the other 18 without EVs) in Austin, Texas, spanning a 12 months period from 1/1/2018 to 12/31/2018. Crucially, the data set is collected with EV traces measured separately so that evaluations can be performed by comparing the estimated EV traces with the ground truths. It is worth clarifying that the use of ground truths is solely for evaluation, and our algorithms do *not* assume the knowledge of these ground truths at all. The temperature data is collected from National Solar Radiation Database (NSRDB) [18].

A. EV Presence Detection

We first present the performance of BTM EV presence detection. As described in Section III-B, for each customer (with or without EV), we run an iterative procedure to compute a) a daily regular (non-EV) load profile $\hat{d}_k(t)$ and b) a set of detected charging periods $\hat{\mathcal{C}}$. Here, for this EV presence detection task, we set csp_{th} and cs_{th} to be $\frac{2\hat{E}_k}{3}$.

We then collect the set of differences $\left\{l_k(t) - \hat{d}_k(t), \forall t \in \hat{\mathcal{C}}\right\}$ (i.e., the raw estimates of charging rates), and examine its statistics to detect whether this customer has a BTM EV or not. In Table I and II, we present the statistics of the sets of differences for the 5 customers with EVs and the 18 customers without EVs, respectively. We expect the statistics for a customer with an EV to be within reasonable ranges: in particular, 1) mean and median charging rates are within (3kW, 4kW). 2) EV customers charge at least 2 hours/week on average. 3) The average temperature over the detected charging periods is within (11.0°C, 28.9°C), i.e. from 20% quantile to 80% quantile of the temperatures in the year of 2018 in Austin, TX. We observe the high performance of our algorithm: a) for the customers with EVs, all of them are successfully identified, and b) for the customers without EVs, 16 out of 18 are successfully identified.

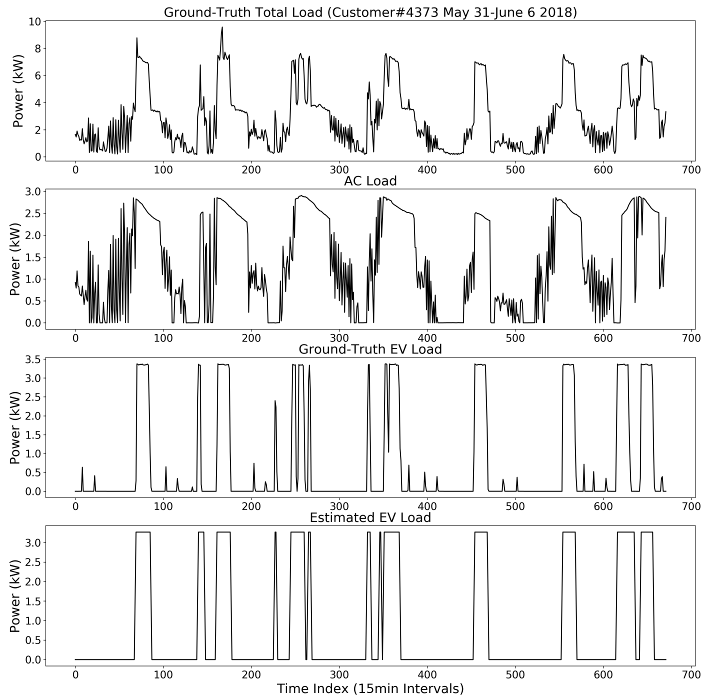

Figure 1: A representative example that shows the disaggregation performance of our algorithm.

Table I: EV Presence Detection (Customers with EVs)

ID	Mean Rate (kW)	Median Rate (kW)	Avg. Charging Hours/Week	Average Temp. (°C)
1642	3.63	3.47	7.87	21.22
4373	3.48	3.30	11.91	21.81
6139	3.27	3.10	5.87	19.16
7719	3.12	3.02	2.70	23.86
8156	3.71	3.49	7.41	21.30

B. EV Charging Rate Estimation and Charging Period Detection

We next present the performance of BTM EV charging rate estimation and charging period detection. Here, a) for the charging rate estimation task, we set csp_{th} and cs_{th} to be $\frac{\hat{E}_k}{2}$ and $\frac{2\hat{E}_k}{3}$, respectively and b) for the charging period detection task, we set csp_{th} and cs_{th} to be $\frac{\hat{E}_k}{2}$ and $\frac{\hat{E}_k}{3}$, respectively.

We summarize the results for the 5 customers with EVs in Table III. We observe that very accurate charging rate estimates are achieved. For charging period detection, a) a binary detection decision of whether an EV is charging is made for each time slot, and b) the true positive rate (TPR) and false positive rate (FPR) over all the time slots are computed as metrics for each

Table II: EV Presence Detection (customers without EVs). Statistics that fail the test of expected EV charging behavior are highlighted.

ID	Mean Rate (kW)	Median Rate (kW)	Avg. Charging Hours/Week	Average Temp. (°C)
2335	3.49	3.42	3.75	25.57
2361	3.13	3.04	5.99	**30.35**
2818	3.55	3.21	**0.03**	18.10
3039	3.33	3.25	6.07	27.19
3456	3.20	3.26	**0.54**	24.41
3538	**2.28**	**2.28**	**0.00**	**0.00**
4031	3.82	3.70	**1.92**	20.81
5746	**2.08**	**2.13**	**0.05**	25.68
7536	3.33	3.18	**1.03**	**30.01**
7800	**2.41**	**2.41**	2.39	28.80
7901	3.78	3.77	**1.61**	22.00
7951	**4.26**	**4.17**	**1.02**	18.14
8386	**2.80**	**2.63**	**0.40**	28.06
8565	**2.89**	**2.93**	2.17	19.72
9019	**2.73**	**2.77**	**0.31**	**32.67**
9160	**2.69**	**2.64**	**0.14**	22.76
9278	**4.34**	3.85	4.46	**10.16**
9922	**4.08**	3..78	3.10	25.46

Table III: Performance of BTM EV Charging Rate Estimation and Charging Period Detection

ID	True Charging Rate (kW)	Estimated Charging Rate (kW)	TPR	FPR
1642	3.38	3.36	0.94	0.03
4373	3.35	3.28	0.92	0.04
6139	3.35	3.23	0.95	0.09
7719	3.27	3.19	0.88	0.03
8156	3.29	3.30	0.88	0.07

customer. From the high TPRs and low FPRs, we observe the high performance of our algorithms. As a representative example, Figure 1 plots the detected EV charging activities compared with the ground truths, demonstrating how the proposed algorithm captures the majority of the EV charging activities by disaggregating the total load trace.

V. Conclusion

In this paper, we developed an effective algorithmic framework that, based on smart meter data of total load traces, a) detects the presence of BTM EVs, b) estimates BTM EV charging rates, and c) detects BTM EV charging periods. The algorithm design successfully exploits a) the characteristics of typical EV charging traces and b) the temporal and cross-customer correlations of non-EV/regular loads. Evaluation conducted on real-world 15-minute interval smart meter data collected from Austin, TX demonstrated great performance of the developed algorithms. BTM load disaggregation for multiple EVs (e.g., at the feeder level) is left for future work.

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